

INTEGRATED DETECTION AND ESTIMATION USING MULTISENSOR AND DISTRIBUTED PROCESSING

RANGASAMI L. KASHYAP

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SCHOOL OF ELECTRICAL
AND COMPUTER ENGINEERING
PURDUE UNIVERSITY
WEST LAFAYETTE, INDIANA 47907-1285

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N. WAHLEN
DTIC Point of Contact

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Integrated Detection and Estimation Using Multisensor and Distributed Processing

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Principle Investigator:
Professor Rangasami L. Kashyap
Kashyap@ecn.purdue.edu Tel: 765 494-3437

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School of Electrical and Computer Engineering
1285 Electrical Engineering Building
Purdue University
West Lafayette, IN 47907-1285

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INTEGRATED ESTIMATION AND DETECTION USING MULTISENSOR DATA

Abstract

This research deals with the solution of detection and estimation problems encountered in a variety of target tracking problems encountered in a Ballistic Missile Defense environment. We propose five broad classes of problems.

The first problem deals with the guidance for interceptors tracking maneuverable targets. We need to forecast the time of intersection and the bearing angle of the target, and have to update them continuously.

The second problem is the robust tracking of moving targets, especially with the tracks close to one another. Our approach avoids the data association lacunae of the existing methods.

Next we deal with targets which can be handled via two-dimensional imagery. We analyze these aspects. First is the method of restoration of degraded images and videos. The second deals with the compression of images and videos by sub-band coding. The third deals with a new approach for handling wavelets and its use in image compression.

I. Introduction

This report contains several new research results of great importance to the SDIO (IST) program. The overall goal of this research is the solution of estimation problems needed for the midcourse guidance of interceptors, identification and initiation of the tracks of the targets, especially maneuvering targets, using not only radar but also two dimensional image sensors. The emphasis is on real-time computation by exploiting parallelism and distributed processing.

We consider five broad classes of problems:

- A) Midcourse guidance for interceptors tracking maneuverable targets.
- B) Robust tracking of moving targets, especially with nearly intersecting tracks, in a distributed framework. We also include wideband target tracking.
- C) Image Restoration. Development of methods for restoration of degraded images and videos so as to display the targets better by not only removing noise, but also sharpening the edges and preserving the information bearing details without introducing excessive computation.
- D) Compression of images and videos by sub band coding.
- E) Methods of decomposing images using wavelets and their compression.

The motivation in both d) and e) is that the compressed images can be transmitted with greater accuracy because their sizes are smaller.

The specific research contributions in these five areas will be described in the next few pages.

Since the result research results have appeared in several archival journals and in the proceedings of prestigious conferences like the International Conference on Signal Processing (ICASSP), we give only a brief, but succinct, description of our research achievements.

II. Details of the Work

Problem (A): Midcourse guidance for interceptors tracking maneuverable targets.

Background:

Perhaps the most challenging task of guidance and control of an interceptor (missile) in pursuit of a highly maneuverable target is that of midcourse guidance [Wang, 1991; Cloutier, 1989]. This consists of estimation of target motion, the generation of guidance commands to optimally steer interceptors toward target intercept and the control of the coupled, nonlinear, multi-variable and uncertain dynamics of the interceptor. Midcourse guidance can be implemented with the target track information being uplinked to the interceptor which uses this information in addition to its self-knowledge obtained from an onboard inertial navigator. Both target and interceptor are tracked by the ground system. For optimal steering, it is desirable to have an algorithm to forecast the Intercept Point (IP) which points the interceptor to a direct collision course to meet the target, thereby reducing interceptor maneuverability. This reduces the amount of propellant required for maneuvering, which is of consequence, especially in Space Based Interceptors (SBI), wherein lofting fuel into orbit is very expensive [Chatterji, 1990]. In [Pachter, 1990], approaches are proposed to predict the intercept point by estimating the target state via Kalman filtering. Here we propose a novel scheme for forecasting the intercept point using the Direction of Arrival (DOA) angle information of both the target and interceptor.

Our Approach

The target and interceptor are assumed to be emitters moving in far field so that their trajectories are characterized by their direction of arrivals (DOAs). Assume a standard linear array of passive sensors. Using the observations from this array, at every instant t , we get 2 estimates of DOA at time t , namely θ_t^1 and θ_t^2 , using standard estimation methods like root-music, maximum likelihood, etc. But the main difficulty is that we do not know whether θ_t^1 belongs to the interceptor or target, especially if we are dealing with a maneuvering target. This is the standard data association lacunae mentioned in the literature.

The key idea is to use the ideas of algebraic geometry [Abhyankar, 1990] and for all observations fit a single curve which has a singularity of the point of intersection. The time of intercept is the time t^* at which the two values of $\theta^1(t^*) = \theta^2(t^*) = \theta^*$. The corresponding time is t^* . The situation is in Figure 1. The simplest curve is the cubic

$$F(\theta, t) = (\theta - \theta^*)^2 - \alpha_0(t - t^*)^2 - \alpha_1(t - t^*)^3 = 0$$

Note that for every t , $F(\theta, t) = 0$ for several values of θ . Only for $t = t^*$, the θ solution is unique, leading to the so-called singular point.

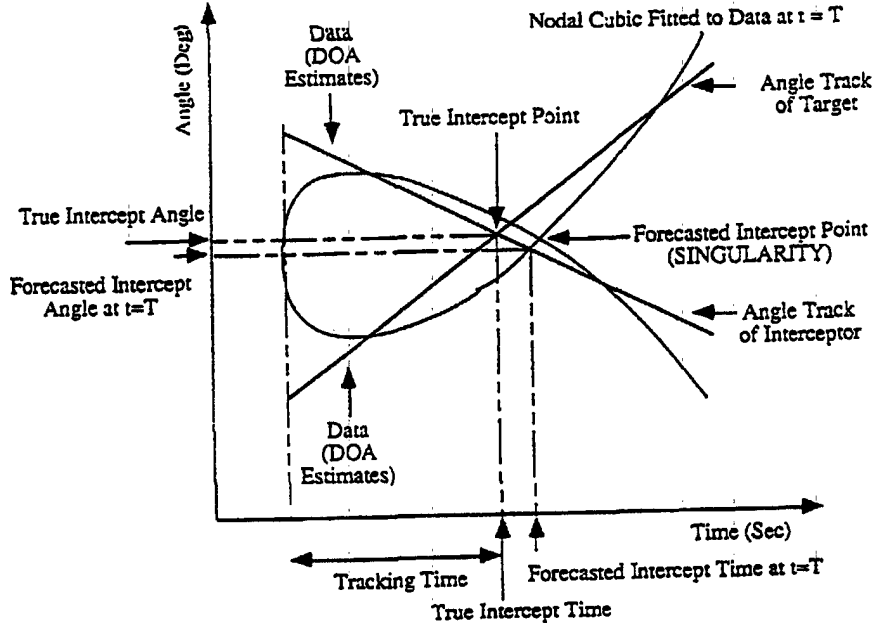


Figure 1

We can write the above cubic as

$$F(\theta, t) = \theta^2 + A\theta + Bt^3 + Ct^2 + Dt + E = 0$$

We fit the $2T$ observation pairs of both interceptor and target obtained until the time T , namely (θ_i^t, t) , $i = 1, 2; t = 1, \dots, T$. By least squares fit, we obtain estimates of the coefficients,

namely A_T, B_T, C_T, D_T, E_T .

estimated angle of intercept using observations until time $T = \theta_T^* = A_T / 2$

estimated time of intercept using observations until time $T = t_T^* T = tT$

$$= -2D_T / 5C_T + \left[0.16(D_T / C_T)^2 + \frac{3(A_T^2 / 4 - E_T)}{5C_T} \right]^{1/2}$$

We can develop a recursive estimation system so that t_T^* and θ_T^* can be continuously updated in real time as new observations come in.

We are also trying to integrate this information with any available information about the dynamics of the interceptor.

The results are given in the publications [1, 6].

Problem (B): Robust tracking of targets

Background:

Consider a passive linear array of M sensors which are uniformly spaced and are separated by a distance d . The number of sensors M is always greater than the number of targets, D . The D targets are assumed to describe arbitrary trajectories in near-field emitting narrowband waves impinging on the array from distinct directions $\theta_1, \theta_2, \dots, \theta_D$ are termed "Direction of Arrival" (DOA) angles. It is required to follow the trajectories of the targets across time as they move in the DOA space.

In sensor array based methods for DOA tracking, estimate association implies association of DOA estimates of different targets at two successive time instants. For the case of D targets, standard state model based methods like track splitting, PDA [Bar-Shalom, 1975], etc., involve searching over the $D!$ possible combinations. The problem with using eigen methods like MUSIC or Root-MUSIC for DOA target tracking is that of estimate association. The dominant eigen values of the data covariance matrix give the DOAs in MUSIC whereas DOAs are obtained by polynomial rooting in Root-MUSIC. Both eigen values as well as the zeroes of the characteristic polynomial do not suggest any ordering of the DOA estimates and hence, there is no way to associate the DOA estimates obtained at an instant with the various targets.

The DOA based method of Sword et al. [1990] avoids the estimate association problem by deriving a recursive procedure for obtaining updated angle estimates at regular intervals of time, whereas the method of Sastry et al. [1991] uses knowledge of signal powers of the targets as additional information and necessarily requires that no two targets have the same signal power for correct estimate association. Both these methods use MUSIC algorithm to obtain estimates of initial DOA and number of targets at regular time intervals. But, the above DOA based approaches do not use target dynamics for obtaining updated target positions in the sense that range and velocity of targets are not estimated.

Our Approach:

We exploit the algebraic geometry approach indicated in Problem (A). Consider the simple case of two targets, $m = 2$. Then we fit a single cubic to the 2T observation pairs (θ_i^t, t) , $i = 1, 2$; $t = 1, \dots, T$, obtained until time T .

$$F(\theta, t) = (\theta - \theta^*)^2 - \alpha_0(t - t^*)^2 - \alpha_1(t - t^*)^3 = 0$$

By using the above data, we can obtain estimates of $\alpha_0, \alpha_1, t^*, \theta^*$, namely $\alpha_{OT}, \alpha_{IT}, t_T^*, \theta_T^*$. Since we have an estimate of the estimated point of intersection, we can devise a simple rule to clarify the two trajectories. For example, many methods cannot identify whether the two trajectories are following the pattern in Figure (i) or (ii). A and B are the two targets.

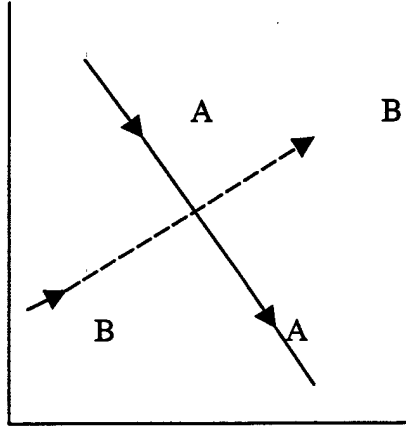


Figure (i)

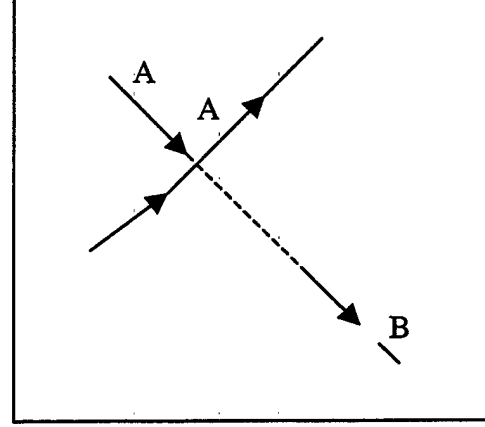


Figure (ii)

In our method we can divide the given observations $\{\theta_t^1, \theta_t^2\}, t = 1, \dots, T$ into four groups. Let us use the label 1 or 2 with the θ estimates meaning $\theta_t^1 > \theta_t^2$, at each time t . The four groups are $\{\theta_t^1\}, t < t^*, \{\theta_t^1\}, t > t^*, \{\theta_t^2\}, t < t^*$, and $\{\theta_t^2\}, t > t^*$.

By Figure (i): target A observations are: $\{\theta_t^{(1)}, t < t^*\}$ and $\{\theta_t^{(2)}, t > t^*\}$ and remaining belong to B.

By Figure (ii): target A observations: $\{\theta_t^1\}$ for all t and the remaining observations: $\{\theta_t^2\}$ for all t belong to B.

A simple curve fitting method and a statistical test can indicate which of the two hypotheses is better.

In our preliminary simulations, this method has performed much better than the other methods, especially when the SNR is low.

When the number of targets m is greater than 2, we need to use fits of higher order having $(m-1)$ singular points. We are exploring this avenue.

Wideband Target Tracking

The proposed scheme for the wideband target tracking problem in farfield is an application of the ML estimation method developed by us earlier. The targets are assumed to be sources of wideband signals impinging on a uniform linear array of sensors. These wideband signals are modeled as vector AR models so that the spectral densities of the targets are characterized by a finite number of AR parameters. The spectral density now becomes a function of these parameters which can be estimated. Defining each target as a "class," we use these estimates and the estimated DOA as components and form a feature vector for that particular class. Estimate association is solved by designing a Bayes classifier. The classifier uses the feature vector so formed and decides as to which DOA should be associated with which particular target. Using this decision, we accomplish target tracking by continuously associating the DOAs of respective targets (classes). However, the efficiency of association and tracking heavily depends on parameterization of the spectral density matrix and estimation of AR parameters. The proposed algorithm will be implemented and compared with other existing wideband techniques for target tracking. The details are in the publication [7] and the thesis by Anantaiyer.

Problem (C): Image Restoration

Background

Digital images are often subject to different kinds of degradations. These degradations may be in the form of additive or multiplicative sensor noise, blur due to camera misfocus or motion, random atmospheric turbulence or bit errors due to faulty communication channels. Therefore, pre- and post-processing units for digital image filtering are an essential part of any integrated vision or imaging system which uses an intensity image as input. These kinds of processing lead to multiple criteria optimization problems that may involve restoration, enhancement, or just a suitable representation of the data and must be capable of satisfying the following requirements:

- restoring the original image from its noisy version (smoothing)
- enhancing certain features (edges) of the degraded image (sharpening)
- preserving the information bearing details of the image (detail preservation)
- can be implemented in real time (computational efficiency)

Most of the traditional methods of image restoration and enhancement are linear and assume an additive Gaussian noise model for the data. These statistical procedures are optimal under exact models of noise distribution, but are generally unstable under small deviations from these models. Moreover, they cannot fully exploit the nonlinearities of the image formation models and human visual system

[Pitas and Venetsanopoulos, 1990]. A well known linear filter is the mean filter. However, if the noise distribution is long-tailed or impulsive, the results are not satisfactory. Another disadvantage of the mean filter is that it tends to blur the edges and eliminate the details of the image and hence it may not be useful as a front end operator in image feature-extraction tasks [Chellappa, 1992]. These disadvantages have led the researchers to use nonlinear filters in a variety of applications.

A popular family of nonlinear image filters is based on the order statistics of the data, i.e., the filter uses the relative ranks of the observation in the data instead of the values of the observations themselves. R-filters and L-filters are well known members which include the alpha-trimmed filter. These filters possess excellent robustness properties in the presence of impulsive noise while preserving the edge information [Pitas and Venetsanopoulos, 1992].

The median filter is the most popular order statistics filter. It can effectively eliminate the effects of impulsive noise while preserving the edge information. However, it also preserves any monotonic degradation of the edge and therefore, is not capable of enhancing blurred or ramp edges. In addition, it often eliminates or disrupts fine details such as thin lines or small objects in the image.

Some researchers have tried to develop a unified theoretical framework for analysis and design of nonlinear filters. Longbotham and Bovik [1989] have used the relationships between order-statistic and linear FIR filters to develop a firm theoretical foundation for order-statistic filters. Coyle, Lin and Gabbouj [1989] showed that stack filters, which are defined by a weak superposition property and an ordering property, contain all composition of 2-D ranked order operations. Finally, Maragos and Schafer [1987] have explored the relationships between the morphological, order-statistic, and stack filters.

Our Approach

We have developed a new type of filter which uses both maximum likelihood reasoning and the reasoning behind the order statistics. There has not been any such work in the field of statistics or filtering. There is one basic advantage in the maximum likelihood approach such as that of Huber's M-estimator [Huber, 1981] which the filters based on the order statistics approach do not possess. In any given data set, most of the data, say a fraction $(1 - \epsilon)$, $0 < \epsilon < 1$, obeys a Gaussian or near Gaussian density p_1 , characterized by parameters θ and the remaining ϵ fraction constitutes the outliers, obeying an impulse like distribution, say $p_2(\cdot)$.

$$p(z) = (1 - \epsilon)p_1(z | \theta) + \epsilon p_2(z) \quad (1)$$

A filter based on order statistics cannot really use the information in equation (1). Consequently, the statistical efficiency of the estimates obtained from order-statistic filters is not high. But the maximum likelihood M-estimate of Huber, which does us

eq. (1), leads to estimates of high efficiency, but it has other drawbacks like its high sensitivity to the scale of the data, etc.

Let the given data set be W , obeying Eq. (1).

$$W = \{z_1, \dots, z_N\}$$

Let W^I be the subset of W which obeys the density p_1 , the so-called inlier set. The remaining constitute the outlier set $W^O = W - W^I$. Assume that the size of W^I is L . Let $E[z | z \text{ obeys } p_1] = \theta$. Then the estimate of θ based on $W^I = \hat{\theta}_I = (1/L)$

$$\sum_{z_i \in W^I} z_i.$$

Since p_1 is Gauss, motivated from the likelihood reasoning, our criterion function is:

$$\begin{aligned} J(W^I) &= \sum_{z_i \in W^I} (z_i - \theta_I)^2 \\ &= \sum_{z_i \in W^I} z_i^2 - \left(\sum_{z_i \in W^I} z_i \right)^2 / L \end{aligned}$$

We will minimize $J(W^I)$ with respect to W^I over all subsets of W of size L . It may appear such a procedure may not be computationally feasible since the number of such subsets is $n!/[L!(n-L)!]$. However, for the univariate data and with inliers obeying an exponential family density function, the optimal subset of size L of candidate inliers can be obtained by comparing only $n-L+1$ contiguous subsets of the rank ordered data according to the following theorems:

Theorem 1: Given a subset W^{NC} of W with size L , which is not contiguous, there always exists a contiguous subset W^C of W with size L , such that $J(W^C) \leq J(W^{NC})$.

The details are in [17, 18, 25] and the thesis by Rabiee.

Problem (D): Compression of video images using subband coding

Background:

There are numerous algorithms for still image compression. There have been attempts at developing standards of data compression in industrial applications. The international committee for setting up standards in this area, the so-called Joint Photographic Expert Group (JPEG), recommended in 1988 [ISO Committee Draft 10918-1] the discrete cosine transform (DCT) based technique for still image compression. The standard for the video compression, which was introduced in 1989

by the Motion Picture Experts Group (MPEG) [LeGall, 1991], is H.261, and this is a motion compensated DCT technique viewed from an algorithmic point of view.

In recent years, increasing demand for HDTV and increasing interest in multimedia showed that the existence of serious limitations in the current standards to cope with the future requirements in new applications. One of the new directions is the introduction of generic coders. Generic coding allows us to define an algorithm to compress the visual data independently of its size, resolution, or the desired compression ration. This requires the introduction of a multiresolution data structure into the actual coding standards, and allows for progressive coding which offers advantages for storage, browsing, and transmitting images over a packet network. The Discrete Cosine Transform (DCT) which is the main building block of all the proposed standard coders is not able to provide an efficient multiresolution data structure. Moreover, if high resolution images are required, the DCT based decoders normally produce blocky images with artifacts that look like ripples spreading out from the edges of the objects [Rabbani and Jones, 1991]. The new techniques for still and video compression include fractal image compression based on Collage Theorem and affine transformations [Barnsley and Lyman], sub-band coding algorithms based on perfect reconstruction filter banks [Gharavi and Tabatbai], discrete wavelet bases and packets [Antonini et al., 1992], and segmentation based techniques such as contour-texture coding [Kung, et al., 1985] and multiresolution BSP coding [Radha, 1993]. A new generation of image and video coding methods based on image segmentation has received a great deal of attention in recent years. Unlike classical coding methods like DCT, the new approaches are based on segmenting the image signal into complex shaped regions. The image signal within these regions or segments, which usually contain real-life objects, can be represented very efficiently. A good segmentation-based method partitions the image into a small number of continuous (smooth) regions such that the image signal within these regions can be represented using few parameters. Therefore, the most challenging aspect of a segmentation based image coding method is to obtain an optimal balance between the number of geometrically simple regions and the smoothness of the image in those regions. The previous segmentation based methods, such as the one proposed by Kunt based on contour-texture coding, have focused only on one of these conflicting requirements. The multiresolution coding of Radha eliminates this problem but is far from being optimal. However, the results are impressive, especially at very low bit rates. This makes this method an attractive choice for video coding. But, this will require development of novel techniques for motion estimation and compensation between successive frames of images to eliminate the interframe redundancies.

The subband coding techniques have been shown to be very effective in image coding applications. In this type of image compression, the original image is decomposed to a set of subband images by a set of filters with different frequency bands (analysis filter bank). These subbands can be coded more efficiently than the entire full band image. The most popular techniques for coding the subband images are: DPCM coding, DPCM/PCM coding, and vector quantization (VQ) coding.

Our Approach

Segmentation Based Subband Coding for Still Image Compression

We want to develop a procedure which has the advantages of both the segmentation method and the subband coding method mentioned above. The key idea is to segment the image, not only at one scale, but at different scales. The recent developments in the efficient design of filter banks and their close relation to the theory of wavelets and multiresolution analysis make this method attractive. An important component of our method is an understanding of the requirements on the filter banks involved.

Some considerations are:

- (i) The short kernel filter requires a smaller number of bits for full precision operations and reduces the amount of memory needed in the system. The delay of subband decomposition is also directly proportional to this parameter. However, this is in conflict with designing filters having very good frequency response through the Heisenberg principle.
- (ii) Phase distortion cannot be tolerated in many image processing applications. Therefore, our filters must have a linear phase characteristic.
- (iii) High pass filters with shorter kernels reduce the aliasing around the edges. In visual data this kind of aliasing is usually more perceptible. The dyadic wavelets are an example of this kind of filter bank.
- (iv) The orthonormality is not a sufficient condition for a good energy compaction. Experiments have shown that in short kernel FIR filter banks, some of the non-orthogonal filter banks perform a better energy compaction than orthogonal filter banks.
- (v) The concept of regularity was introduced in conjunction with the theory of wavelets. A filter bank is regular if its impulse response tends to a continuous function as one goes higher in the multiresolution pyramid. In image processing applications some degree of regularity is desired to avoid fractal-like behavior of the short kernel filters.
- (vi) The filter banks must be easy to implement and computationally efficient.

After selecting the optimal wavelet bases for subband decomposition, we would need to design an algorithm for efficient segmentation of the images in different scales. The most challenging aspect of the segmentation based coding is to obtain an optimal balance between the number of geometrically simple regions and the smoothness of the image in those regions. We are investigating the possible use of multiscale Markov random field models (MRF) and the autoregressive (AR) models. The PI is one of the pioneers in this area [Kashyap & Chellappa, 1982, 1983, 1991; Kashyap, 1984; Delp & Kashyap, 1979].

The details of our results are in [24, 26, 27].

Motion Compensated Segmentation Based Subband Coding for Image Sequence (Video) Compression

Our approach in video coding is a hybrid one, handling the spatial and time components separately. The spatial component (i.e., coding within an image) is performed by the segmentation based subband coding described in the previous section. To reduce the interframe (temporal) redundancies we will use a motion compensated coding technique. The motion compensation (MC) technique achieves a high degree of reduction by estimating the motion of the pixels within a given frame relative to the pixels of a reference frame [Netravali, Haskett, 1988]. The MC techniques can be classified into two distinct categories: Block Matching (BM) and recursive techniques. In recursive techniques, the motion is estimated on a pixel-by-pixel basis, whereas in the BM methods, the motion is estimated on a block-by-block basis in an independent fashion. Although the recursive techniques have a better performance in terms of estimation of motion parameters, they are computationally extensive and harder to realize in hardware architectures. We are naturally using a BM technique for motion compensation, since our intraframe coding was based on segmentation. Our biggest challenge is to devise an algorithm for MC that is capable of estimating the motion parameters of our nontrivial (in geometry) segments at different resolutions. The recent work by Zhang [1992] has shown that the discrete wavelet transforms have great potential in estimation of the motion parameters at different resolutions. We are also considering the packet wavelets [Coifman & Wickerhauser, 1990]. This will give us one more degree of freedom to compare to the wavelets, namely the frequency. The results are in the thesis by Rabiee and also in [27].

Problem (E): Decomposition of Natural Images Using Wavelets

The focus of this thesis is to explore the structure present in the wavelet decomposition of natural images and use this structure for image compression and representation.

We first show empirically that the wavelet coefficients of a natural image, when sorted by magnitude, lie almost exactly on a curve of the form $\frac{1}{x^a}$. This, in turn,

helps us to demonstrate that natural images may exhibit self-similarity in the wavelet domain, although no such property may be apparent in the pixel domain. We have developed a top-down adaptive search (TAS) algorithm which provides an adaptive, structured methodology for selecting dilates and translates of the wavelet. The TAS algorithm is useful because it enables us to predict (i) the *positions* of the significant coefficients and (ii) the *magnitude* of the coefficient. We use the TAS algorithm together with a data structure called a “web” which we define.

- show that the TAS algorithm automatically zooms in onto the edges present in the image.
- show that the TAS algorithm yields a number (we call it γ), which is indicative of the amount of structure present in the image. We also derive a theoretical upper bound on the value of γ that will result when the algorithm is applied to an autoregressive process. This theoretical bound further supports the empirical evidence that γ is indicative of the amount of structure in the image.
- propose an algorithm for image compression that
 - allows the user to control both the mean square error and number of coefficients,
 - has performance comparable to the best available algorithms,
 - has low computational requirements,
 - yields a conditionally embedded bitstream,
- formulate a wavelet-based stochastic process which can serve as an image model. For the stochastic process, we
 - prove its existence
 - derive necessary and sufficient conditions for the process to have finite energy.
 - prove that it provides infinite details everywhere

The results are in the publications, [3, 8, 14, 19, 20, 21, 22, 23, 28]

(F): Automatic Segmentation of Images

An important problem in the target tracking via two-dimensional imagery is the need to partition the given image into several segments so that each segment has only one target or artifact. The published papers [31, 32, 33] deals with this topic.

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